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Development of a fleet emissions control (FEC) framework for passenger cars

Md Saniul Alam [a, *], Aonghus McNabola [a, b]

[a] Dept of Civil, Structural & Environmental Engineering, Trinity College Dublin, Dublin, Ireland

[b] Global Centre for Clean Air Research, Department of Civil and Environmental Engineering, Faculty of Engineering and Physical Sciences (FEPS), University of Surrey, Guildford, GU2 7XH, United Kingdom

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A B S T R A C T

The composition and size of the passenger car fleet is often influenced by legislation and policy, including taxation, scrappage, and vehicle registration policies. Numerous measures at national and international level have been investigated to reduce the air pollution and/or climate change impacts of passenger fleets. However, the objectives of climate change and air pollution policy occasionally are conflicting, and this has resulted in a number of well publicised policy shortcomings. This paper outlines the development of a fleet emissions control (FEC) framework which enables the dynamic and adaptive optimisation of fleet emissions through changes in taxation policy in Ireland. The data for analysis was obtained from national sources including datasets from the national emission inventory and COPERT model. Applications of regression-based modelling and statistical analysis were conducted to predict fleet, mileage, and emissions changes. The results of the FEC framework showed that no increase in NO_x emissions, above 2007 levels, could be achieved at a cost of a small increase in CO_2 in 2016 (+1.8%). This could be achieved by taxation policy primarily resulting in a shift away from small engine diesel vehicles (<1.4 L) in the fleet which were responsible for the largest contribution to emissions. In the transition of vehicle fleets to full electrification or full decarbonisation, the FEC framework developed here offers the potential to formulate practical and optimised adjustments in static taxation systems. These adjustments will assist in achieving the requirements of national policies on reducing emission.

1. Introduction

The engineering of vehicle fleet size and composition has been conducted at national and international level to achieve improvements in the production of harmful emissions and to enable a cleaner transportation system. This engineering has been achieved through different taxation policies, fleet renewal policies, and vehicle registration policies. These policies have achieved energy, cost and/or emission savings (Giblin and McNabola, 2009; Li et al., 2015, 2018; Yang et al., 2014). Direct interventions to control light duty and heavy-duty vehicles have been reported in the literature (Li et al., 2015, 2018; Fuel Cells Bulletin, 2018; Tang et al., 2017). Bus fleet management in terms of early-retirement of vehicles, or retrofitting and replacing diesel with electric vehicles (Li et al., 2015, 2018) to reduce cost or emissions has also been investigated. Adding low emissions vehicles to the fleet is also a strategy to reduce emission levels (Fuel Cells Bulletin, 2018). However, retrofitting or fleet renewal is difficult to implement for passenger cars as they are not often operated at company level or by national authorities. The control over these passenger cars is often guided by vehicle taxation and fuel policies.

In Ireland, an incentivisation of diesel passenger cars was introduced in 2008 to reduce CO_2 emissions through a taxation reform, helping to comply with EU emission reduction targets (Leinert et al., 2013). Passenger cars (PCs) were the largest vehicle category in the Irish fleet accounting for the highest mileage share (77.3%) (EPA, 2018). PCs were also responsible for the highest portion of emissions to the air of all vehicle categories. The 2008 diesel incentivisation was achieved through changes in the Motor Tax (MT) and Vehicle Registration Tax (VRT) for new vehicle purchases (Alam et al., 2017a, 2017b). MT and VRT were altered to be based on CO_2 emissions rate instead of engine size (Giblin and McNabola, 2009). As new diesel engined PCs typically had significantly larger engines but slightly lower CO_2 emission rates than

* Corresponding author.
E-mail address: alamms@tcd.ie (M.S. Alam).

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petrol equivalents in 2008, the policy encouraged growth in diesel vehicle sales. Previous research predicted initial benefits of CO_2 reduction (Rogan et al., 2011; Hennessy and Tol, 2011) due to this dieselisation; however, a 28% increase in NO_x emissions by 2020 as a result of the implementation of this policy compared to 2008 levels, was also predicted (Leinert et al., 2013). Similar policies were introduced in several EU countries. For example, Degrauewe et al. (Degraeuwe et al., 2017) outlined the effects of increased diesel vehicle emissions on NO_2 concentrations in street canyons in European cities.

Bollen and Brink (2014) highlighted that a nexus often exists between policy focused on climate change and CO_2 emission reduction, and policy focused on air pollutants and public health, as has been the case in the road transport sector. Considering these objectives in isolation has led to a number of well documented policy failures. Considering both greenhouse gases and air pollutants together, investigations have highlighted the potential co-benefits that can be achieved (Bollen and Brink, 2014). Positive impacts of the electrification of the fleet have been reported, both in terms of air pollution and climate change objectives (Rangaraju et al., 2015; Nanaki and Koroneos, 2013). However, barriers exist to widespread electrification of the road transport fleet (Contestabile et al., 2017), and an optimised fleet composition using a balance of all available vehicle technologies should be considered as an interim/transition measure for addressing climate change and air pollution issues, prior to fuel electrification of the fleet.

In this paper, an adjustment in taxation policy was investigated to find a balance in the composition of the fleet. This balance restricts fluctuations in the level of growth of different types of emissions, moving towards an optimum fleet emission mix from both air pollution and climate change perspectives through a proposed Fleet Emissions Control (FEC) Framework. In the FEC framework, emission types with the highest priority set by policy makers, govern the future fleet composition. In the process, emission trade-off rates for priority emissions was a key factor to shift mileage from higher to lower emission engine sizes, in the nearest engine size category, and within the same fuel type. An optimal fleet share and corresponding mileage in terms of lower harmful emission is the major output from the FEC Framework. The fleet share or a trend of the time series mileage can be derived for future years using macro-economic data and these may be used as an indicator for future adaptive changes in taxation systems.

The research most relevance to this study were conducted by Fontes & Pereira (Fontes and Pereira, 2014) and Leinert et al. (2013). Fontes & Pereira (Fontes and Pereira, 2014) compared a baseline scenario against 'what-if' scenarios representing fuel pricing, car scrappage, and car taxation in an ex-post analysis similar to this study. In this study, changes in emission factors in scenarios were modelled in detail rather than the fleet and mileage. Leinert et al. (2013) conducted a similar study in Ireland, however, the focus of that work was to present on what would happen in future (2020) for only NO_x and CO_2, as a result of the diesel taxation reform. The fleet and mileage were modelled using a car stock activity model (Leinert et al., 2013). In addition to such comparisons, this paper provided a major step forward in showing how this knowledge can be utilised to reduce future emission applying the FEC framework.

2. Methodology

2.1. Methodological steps

This paper comprised the development of the FEC framework through the modelling of three emissions scenarios:

i) The present-day 'baseline' scenario;
ii) 'what-if' scenario, assessing the impacts of dieselisation and helping to develop the basis for the FEC;
iii) 'optimised emission' scenario applying the developed FEC framework.

The three emissions modelling scenarios were applied to the national road transport emissions data from Ireland over the period 1990 to 2016. Similar policy impact studies (i.e. a comparison between i) baseline and ii) what-if scenarios) were conducted forwards and backwards in time in (Alam et al., 2017b; Fontes and Pereira, 2014).

In this study, the emissions from the 'baseline' scenario were first compared against the emissions modelled under the 'what-if' scenario. Only emission types under United Nations Framework Convention on Climate Change (UNFCCC) United Nations Economic Commission for Europe (UNECE), for road transport were considered. To construct the 'what-if' scenario, the fleet and mileage data were reconstructed to represent what would have happened without the introduction of the diesel vehicle incentives in Ireland in 2008 (i.e. the continuation of the 2008 taxation policies to 2016). The fleet size and the total mileage remained the same, based on an assumption that the economic growth of the country would be unhampered if total mileage remained the same. Emissions modelled from the 'what-if' scenario were compared against the baseline scenario, and Implied Emission Factors (IEF) were generated (see Section 2.3). The aim of this comparison was to enable the assessment of changes in taxation policy over an extended time series, as opposed to comparing changes at the beginning and end of a given time period as previously conducted (Leinert et al., 2013; Fontes and Pereira, 2014). Facilitating a comparison of changes in emission arising from taxation changes year-on-year could enable the development of more dynamic and adaptive taxation systems, capable of responding to emerging trends in the data.

A FEC framework was subsequently developed from the aforementioned comparison, where an optimum fleet could be determined based on the contributions of the two highest priority pollutants. The composition of the future fleet predicted by the FEC to enable this optimum fleet emission can be used as an indicator for more dynamic refinement of current taxation systems. Priority on the emissions were set based on emission reduction targets at national level. This third 'optimised emission' scenario was therefore developed under the FEC framework which aimed to optimise future emissions. The steps in the analysis are presented in Fig. 1.

2.2. Data sources

The major source of data in this research was collected from the emission inventory of the Irish Environmental Protection Agency (EPA) from 1990 to 2016 (EPA, 2018). The disaggregated fleet and mileage data by emission standard, fuel type, and engine size for PCs were collected using COPERT 5 software. The estimated emissions for gasoline and diesel PCs were also obtained and termed as the 'baseline scenario'. Mileage for other vehicle categories were neglected as they represented less than 0.09% of the fleet (EPA, 2018).

Several other types of data were required for the mileage adjustment stage (see section 2.5). These data were collected from government agencies from 1990 to 2016 and are presented in Table 1. The other country-specific modelling parameters were kept identical to the 'baseline' scenario throughout this study (e.g. traffic speed, peak and off-peak shares, share of urban, rural and highway mileage, etc). These were also described in previous studies (Alam et al., 2017a, 2017b). In addition to these, the total PCs fleet size (TOT) which was a sum of petrol and diesel PCs was also applied as

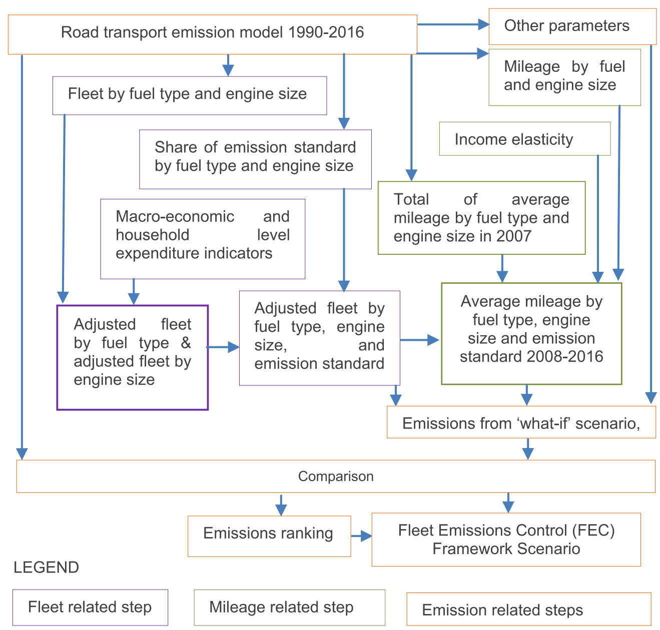

Fig. 1. Analytical approach.

an indicator in fleet modelling stage (see section 2.4).

2.3. IEF

An IEF is defined as emissions divided by the measure of corresponding activity that cause the emissions to be generated. IEFs are estimated following Eqn (1) where a particular type of emission (EM) released in the atmosphere from a fleet type (n) can be estimated from fleet size (F_n), and average mileage for that fleet type (M_n).

$$IEF_{n,EM} = \frac{EM_n}{F_n.M_n} \quad (1)$$

When fleet type (n) is subdivided by fuel type (f) and engine size (z), the IEF takes the following form in Eqn (2). An implied emission factor is defined as emissions divided by the relevant measure of activity:

$$IEF_{f,z,EM} = \frac{EM_{f,z}}{F_{f,z}.M_{f,z}} \quad (2)$$

2.4. Fleet modelling

Eleven macroeconomic, household level expenditure and tax-related indicators from Table 1 were assessed in the 'baseline' scenario for their correlation with fleet size and composition between 1990 and 2016. The selected indicators were then applied to model the fleet under the 'what-if' scenario, whereby the 2008 to 2016 diesel incentive was not implemented during the 1990 to 2016 period (1990–2007 remained unchanged).

In the 'what-if' scenario, the fleet modelling was conducted in a two-stage process. In the first stage, a shift in the fleet from petrol to diesel passenger car (PC) categories was modelled to calculate the fleet size. A shift of engine size was then modelled in the second stage (see Table 3). In both stages, the last vehicle category (nth) was not modelled, these ($F'_{n^{th}}$) were estimated from the subtraction of the summed modelled fleet categories ($\sum_{0}^{n-1} F'_n$) from the total fleet (F_n). This (n-1) modelling approach was adopted to keep the total fleet size the same as the 'baseline' scenario.

The two-stage fleet modelling was carried out through a regression analysis. The uninfluenced fleet sizes by fuel or by fuel and engine size before the dieselisation reform were regressed against suitable indicators from 1990 to 2007 (e.g. GDP, population, employment). The developed regression models were applied for the prediction of fleet categories from 2008 to 2016 without the influence of the diesel incentive. Regression analysis has previously been applied in fleet modelling of this nature (Alam et al., 2017a, 2017b; Hao et al., 2015) in the form of Multiple Linear Regression (MLR) shown in Eqn (3).

$$\begin{aligned} F_n &= C_0 + A_1 \cdot X_1 + A_2 \cdot X_2 + ... + A_n \cdot X_n + F \\ &= C_0 + A_1 \cdot X_1 + A_2 \cdot X_2 + ... + A_n \cdot X_n + \end{aligned} \quad (3)$$

Where, F_n = Fleet size in a category; C_0 = Intercept; X_n = nth predictor variable; A_n = regression coefficient for the nth predictor variable; $\in$ = Error.

The fleet size by fuel type was modelled in the first stage, whereas the percentage share of the fleet categories by fuel and engine size were modelled in the second stage. This was to facilitate calculating disaggregated fleet by fuel and engine size, after the

Table 1
Data types and sources.

Data	Code	Unit	Source	Applied as/for*
Gross National Product	GNP	2014 market prices in € millions	CSO (2018)	Obtained/M
Gross National Product per '000 population	pGNP	2014 market prices in €	CSO (2018)	Derived/M
Population aged over 15 years	POP	'000	CSO (2018)	Obtained/M
Gross Domestic Product	GDP	Current US$	WB-World Bank (2016)	Obtained/M
Annual GDP growth	gGDP	Percentage (%)	WB-World Bank (2016)	Obtained/M
Employment to population (age 15+) ratio	EMP	Ratio	(CSO, 2018; WB-World Bank (2016))	Derived/M
Final consumption and expenditure	C&E	Percentage of the GDP (%)	WB-World Bank (2016)	Obtained/M
Household final consumption and expenditure	hC&E	Constant 2010 US$	WB-World Bank (2016)	Obtained/M
Annual growth of household final consumption expenditure	gHCW	Percentage (%)	WB-World Bank (2016)	Obtained/M
Average Vehicle Registration Tax **	VRT	€	(DEHLG, 2008; Hennessy and Tol, 2009))	Derived/M
Fuel price for petrol and diesel	P	€/'000 L	EPA (2018)	Obtained/A
Average Motor Tax **	MT	€	(DEHLG, 2008; Hennessy and Tol, 2009)	Derived/M
Income Elasticity of Mileage	I	Numeric figure	(Hennessy and Tol, 2009; Daly and Ó'Gallachóir, 2011)	Obtained/A

*Data were directly obtained or derived from two or more sources for the assessment of fleet modelling (M), or mileage adjustment (A). ** For petrol and diesel PCs in relation to the engine sizes defined in COPERT model.

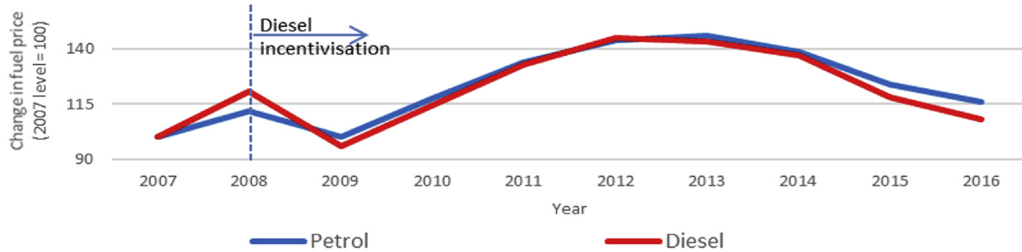

Fig. 2. Average change in price of fuel 2007–2016.

calculation of the nth fleet from both stages. Following this process, one fleet category was modelled in the first stage and two categories were modelled in the second stage.

2.5. Mileage adjustment

An income elasticity for mileage of −0.3 for smaller engine size vehicle categories (Hennessy and Tol, 2009), and a zero value for higher engine sized PCs were applied in conjunction with the fuel price (Fig. 2) on the baseline mileage of 2007. Changes in fuel prices in the modelling period was influenced by the changes in the economy (see gGDP in Fig. 3). Changes in later years for diesel price was also noticeable which further influenced dieselisation. The later assumed no impact of fuel price on vehicle use for larger engine PCs as per (DEHLG, 2008).

The original average mileage (M) by emission standard ($e = 0$ *for conventional; 1–6 for* EURO emission standards 1 to 6), engine size (z) and fuel type (f) were expressed as $M_{f,z,e}$ and these notation keys for disaggregation of mileage have been applied to Eqns. (4)–(8). $M_{f,z,e}$ data was available for 1990–2016 in the COPERT 5 database for the 'baseline' scenario. In the 'what-if' scenario, mileage adjustment was carried out in a three-step procedure to match the same level of disaggregation of mileage from the 2008–2016 'baseline' scenario. The 'what-if' scenario mileage was predicted at fuel and engine size level first, and in the next step the mileage was disaggregated by emission standard, fuel and engine size. Finally, the estimated mileage was adjusted to the total mileage.

To predict the mileage by fuel and engine size in future years ($\overline{M_{f,z}}$) the 'baseline' mileage ($M_{f,z}$) of 2007 was considered as a function of income elasticities (I_z) of mileage by engine size, and of the fuel price (P_f) for future years as shown in Eqns (4) and (5) (Hayashi et al., 2001). This was conducted to reflect the fleet change impact and vehicle use decisions in the 'what-if' scenario.

$$\overline{M_{f,z}} = f\left(M_{f,z}, I_z\right) \tag{4}$$

The total average mileage of all emission standards at the level of fuel and engine size ($\overline{M_{f,z}}$) for 2008–2016 under the 'what-if' scenario was derived from Eqn (5):

$$\overline{M_{f,z,\,(t+1)}} = \left(1 + I_z \cdot \left(1 - \frac{P_{f,(t+1)}}{P_{f,t}}\right)\right) \cdot M_{f,z,t} \tag{5}$$

Predicted total average mileage by fuel and engine size was then distributed to the emission standard level. Predicted total mileage by fuel, emission and engine size was calculated using the fleet size from the 'what-if' scenario in Eqn (6).

$$\overline{T_{f,z,e}} = F'_{f,z,e} \cdot M_{f,z,e} \cdot \frac{\sum_{e=0}^{e=6} M_{f,z,e}}{\overline{M_{f,z}}} \tag{6}$$

Finally, the average mileage by fuel, engine and emission standard ($M'_{f,z,e}$) under the 'what-if' scenario was derived following Eqn (7). In this equation, a yearly adjustment factor (n) was applied. This factor is a ratio between the total original mileage in a year and the predicted total mileage in a year across all vehicle categories in Eqn (8). This equation ensured that the total mileage produced by this step, remained the same as the 'baseline' scenario.

$$M'_{f,z,e} = n \cdot \overline{T_{f,z,e}} \cdot \frac{1}{F'_{f,z,e}} \tag{7}$$

Where,

$$n = \frac{\sum T_{f,z,e}}{\sum \overline{T_{f,z,e}}} \tag{8}$$

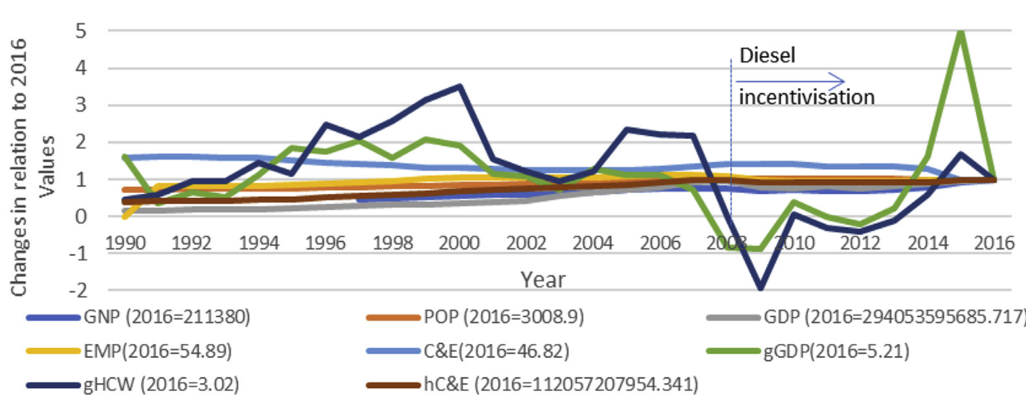

Fig. 3. Time series data in relation to their values in 2016.

2.6. Fleet emissions control (FEC) framework

The impact on total fleet emissions caused by a switch of one unit of a vehicle category to another could be calculated from a comparison of the 'baseline' and 'what-if' scenarios. Priority emissions and pollutants can be determined through national emission reduction targets or based on their weighted negative impacts on public health and the environment. In the FEC framework developed here, two emission types with the highest priorities were selected from the 'what-if' and 'baseline' scenario comparison. This was conducted to monitor the emissions impact of shifts between different vehicle technologies. When satisfactory levels of emissions can be obtained, the fleet composition can be considered as an optimal fleet composition for a given year. Optimal fleet composition in every historic year can be applied with macroeconomic data to project an optimum future fleet composition to indicate the changes required in the current taxation policy.

The optimal fleet composition here is considered in strongly practical terms, whereby only changes in vehicle fleets that could be reasonably achieved by changes in the taxation system were considered. Clearly, shifting all vehicles to the smallest engine size and highest emission standard would be most optimal, but not practicable. For this reason, the FEC serves as an interim methodology to optimum fleet composition during the transition towards electrification or de-carbonisation by other means. The FEC operates to shift mileage to the lowest category of emitters and their total mileage will then be converted to fleet size. This fleet size will be used as an indicator in changing the VRT and MT. The time series in the policy period will be calculated year by year. Assumptions and steps are as follows:

1. Types of emission with the highest national priority should be set as the target pollutants and the aim of the FEC will be to nullify the difference in the target pollutant between two scenarios. Previous research reported nonlinear impacts on the reduction of different types of emission in response to policy changes (Fontes and Pereira, 2014), thus the selection of targeted emission types simplifies the analysis in the Framework.
2. Targets for shifting mileage should always be achieved within the same fuel type and nearest engine size. This will assist in the practical implementation of the proposed new policies. People will be less sensitive to a smaller change in vehicle size.
3. Optimisation is focused on changes to the 'baseline' scenario as there is less uncertainty and fewer analytical steps.

To implement the findings, the fleet sizes in the future years will be used as indicators. The elasticity of MT and VRT to engine size of the vehicle need to be estimated, and MT and VRT will be adjusted based on elasticity and indicators.

3. Results of scenario comparisons

3.1. Fleet modelling

At the first stage of fleet modelling, the indicators in Fig. 3 were assessed for their ability to predict petrol PC fleet size. The Pearson correlation coefficient (r) of the indicators in relation to the PC fleet (petrol) are shown in Table 2.

In the second stage, the share of engine size by fuel for PCs was modelled. Three fleet types by engine size for petrol and diesel fuel categories were modelled after assessing the variables in Table 3. The fleet sizes for the remaining categories were estimated using an (n-1) approach. Along with MT and VRT, three additional indicators were assessed and their Pearson correlation coefficient was given in Table 3.

The gasoline and diesel PC fleets in the COPERT model had a disaggregation among seven emission standards (conventional & EURO emission standards 1 to 6). The share of emission standard by fuel type and engine size was considered unchanged. This was based on an assumption that the purchasing time of the vehicle would not be interrupted in the 'what-if' scenario. This share was applied to the disaggregated fleet by the fuel and engine sizes predicted in the two-stage process. This yielded a fleet disaggregated by fuel, engine size and emission standard. The determination of emission standard and vehicle purchase year was previously modelled in (Alam et al., 2017a).

From Table 1, the hC&E and GDP indicators were selected by a forward selection procedure in the regression model to explain the time series variation of the petrol fleet from 1990 to 2007, on the basis of their Pearson correlation coefficients. The maximum Variance Inflation Factor (VIF) was <2.2, and the adjusted coefficient of determination and its validation (both $R^2 = 0.99$) were acceptable. The developed model for the petrol fleet size in the 'what-if' scenario is shown in Eqn (9). The model was applied to the indicator data from 2008 to 2016 to estimate petrol PC fleet size. The diesel PC fleet was calculated from the total PC fleet and is shown in Fig. 4. The 22,457 vehicles shifted from diesel to petrol PCs in 2008, which gradually increased to 542,140 in 2016.

$$\acute{F_p} = -17070000 + 723800 \cdot \log(hC\&E)$$

Table 2
Pearson correlation coefficients, r: petrol PC fleet size vs. indicators.

Indicators	r	Included in Model
GNP	0.26	No
GDP	0.78	Yes
C&E	−0.052	No
gHCW	−0.17	No
POP	0.85	No
EMP	0.87	No
gGDP	−0.032	No
hC&E	0.87	Yes

Table 3
Average MT and VRT.

Category	Modelled	MT (€)			VRT (%)		
		Before 2008	After 2008	r	Before 2008	After 2008	r
Petrol <1.4*	Yes	231.3.	179.5.	−0.48	23.1.	16.5.	−0.48
Petrol 1.4–2 L**	Yes	440.3.	508.0.	−0.51	25.0.	25.3.	−0.51
Petrol >2 L	No	975.0.	1575.0.	−0.36	30.0.	34.0.	−0.36
Diesel <2***	Yes	320.9.	169.4.	0.59	23.9.	16.3.	0.59
Diesel >2	No	975.0.	1325.0.	0.59	30.0.	32.0.	0.59

*r: (POP = −0.13, TOT = −0.57, pGNP = 0.34); **r: (POP = 0.07, TOT = 0.51, pGNP = −0.42); ***r: (POP = −0.86, TOT = −0.42, pGNP = −0.33).

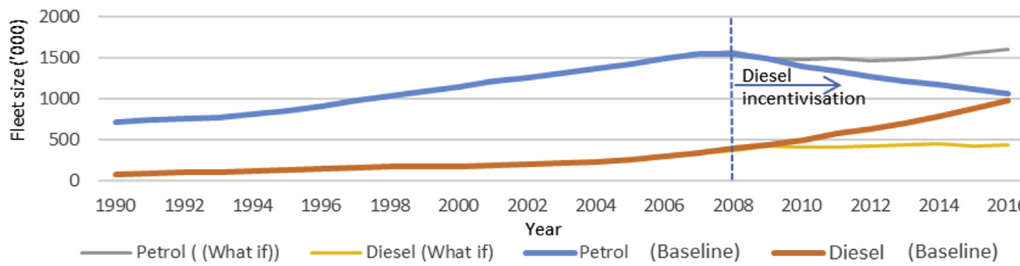

Fig. 4. Fleet size from 1990 to 2016: 'Baseline' and 'what-if' Scenarios.

Table 4
'What-if' scenario fleet model performance measures.

$$F'_{p<1.4} = 1.022 - 0.0012440000 \cdot MT - 0.0000001271 \cdot TOT + \in_{<1.4} \quad (10)$$

$$F'_{p1.4-2} = 0.5888000000 - 0.0007121 \cdot MT + 0.0000000880 \cdot TOT + \in_{p1.4-2} \quad (11)$$

$$F'_{D<2} = 1.763 - 0.185 \cdot \log(GNP) + 0.0007041 \cdot MT + 0.000000273 \cdot TOT + \in_{D<2} \quad (12)$$

Fleet	VIF	adjusted R^2	validation R^2
$F'_{p<1.4}$,	1.17	0.90	0.95
$F'_{p1.4-2}$	1.17	0.93	0.92
$F'_{D<2}$	6.5	0.88	0.95

$$+0.0000008756 \cdot GDP + \in_p \quad (9)$$

Where, F_p = Fleet size of the petrol PC; $\in$ = Error.

Fleet size data from 1990 to 2007 was modelled in the first stage of fleet modelling and baseline indicator values were applied for prediction in the period 2008–2016. Fleet shares from 1990 to 2016 were modelled in the second stage, using the baseline indicator values. In the prediction of the share of fleets for the 'what-if' scenario, the MT and VRT indicators were kept constant for the post-2007 years (see Table 3).

The resulting models for the $F'_{p<1.4}$, $F'_{p1.4-2}$ and $F'_{D<2}$ fleets in the 'what-if' scenario are presented in Eqns (10)–(12). The maximum VIF, adjusted R^2 and the validation R^2 for these models are shown in Table 4.

The $F'_{p>2}$ and the $F'_{D>2}$ for Petrol >2 L and Diesel >2 L in 'what-if' scenario were calculated from these equations ($F'_{p>2}$ = 1-$\sum_{p<1.4}^{p1.4-2} F'_p$; $F'_{D>2} = 1 - F'_{D<2}$) and the results were presented in Fig. 5a and (b).

In the 'what-if' scenario for the petrol PC in Fig. 5a, the share of the smallest engine size was reduced by a rise in other engine sizes. Whereas, the opposite phenomenon was noticed for diesel vehicles (Fig. 5b). However, this gap closed in 2015 and purchasers were predicted to buy higher engine sized diesel PCs in 2016, compared to the historical trend. This could be related to the strong economic recovery in Ireland during this time. The share of fleets by fuel in Fig. 5 was multiplied with the fleet size by fuel in Fig. 4, and the baseline share of fleet emission standard, to estimate the most disaggregated fleet (see Fig. 6). It was noticeable that the petrol PCs in Fig. 6, especially lower engine sized PCs, increased in comparison to the baseline scenario in Fig. 4.

3.2. Mileage comparison

From the mileage adjustment process, an increase in average mileage per vehicle category was noticeable for Figs. 7 and 8. As the price of the fuel started to decline in 2012, the mileage increased. In the last two years, the mileage for all vehicles increased, especially for the diesel vehicles in Fig. 8, reflecting that the price decline rate of diesel fuel price was higher than that of petrol. In addition, the increase of mileage was also higher for PC engine sizes >2 L as they were modelled as inelastic to fuel price.

3.3. Emission and implied emission factor comparison

Emissions in the 'what-if' scenario in Fig. 9 show that there would have been three different trends in the time series of emission changes, with respect to the emissions level of 2006. Some pollutants (e.g. $PM_{2.5}$ and NO_x) would have increased immediately, followed by a decrease later. While changes for N_2O would have gradually decreased from the year 2007. These changes were related to vehicle emission factors improvements which have occurred during this 9-year period (Alam et al., 2017a).

CO_2 would have increased, gradually decreased, and would have started increasing again. CO_2 emission is directly related to fuel consumption which in turn is highly related to the economy, e.g. emission reduced during the economic recession period (2008–2011), increased during the economic recovery (2011–2014), and increased further during the strong economic growth period (2014–2016) in Ireland.

When predicted emission results were compared against the 'baseline' scenario, the following difference was found in Fig. 10. The results show that the difference would be approximately a 5.4% increase of CO_2 and 6.4% for $PM_{2.5}$ in 2016 without the implementation of the 2008 diesel incentives. NH_3, CO, NMVOC and CH_4 would also have been increased by 50.9%–61.9%. The nitrogen-based emissions, however, would have reduced by 22.8% for NO_x and 19.9% for N_2O.

This estimation is also in line with previous predictions on the impacts of the diesel incentive on NO_x emissions. A 28% higher NO_x emission was estimated in 2020 in relation to a similar "what-if" scenario (Leinert et al., 2013). The results of this estimation highlight that the diesel incentive has been successful in slightly reducing CO_2 as intended. The results also shows that the diesel incentive has slightly reduced $PM_{2.5}$ emissions, due to a shift to smaller engine size vehicles as well as improved IEFs for EURO 5 and EURO 6 diesel PCs. The major shortcoming of the policy is the very large increase in nitrogen-based emissions.

IEFs (g/km) that were generated from the results and input data were found to be the same for the two scenarios. The IEFs for CO_2 and NO_x as representatives of positive and negative impacts on fleet emission are shown in Fig. 11. These were considered for developing a FEC framework as the highest priority pollutant types, representing both the climate change and air pollution perspectives.

It is noticeable that all the CO_2 IEFs for petrol PCs were gradually increased (Fig. 11a), especially after 2011, whereas the NO_x IEFs were gradually decreased for the same categories (Fig. 11b). The

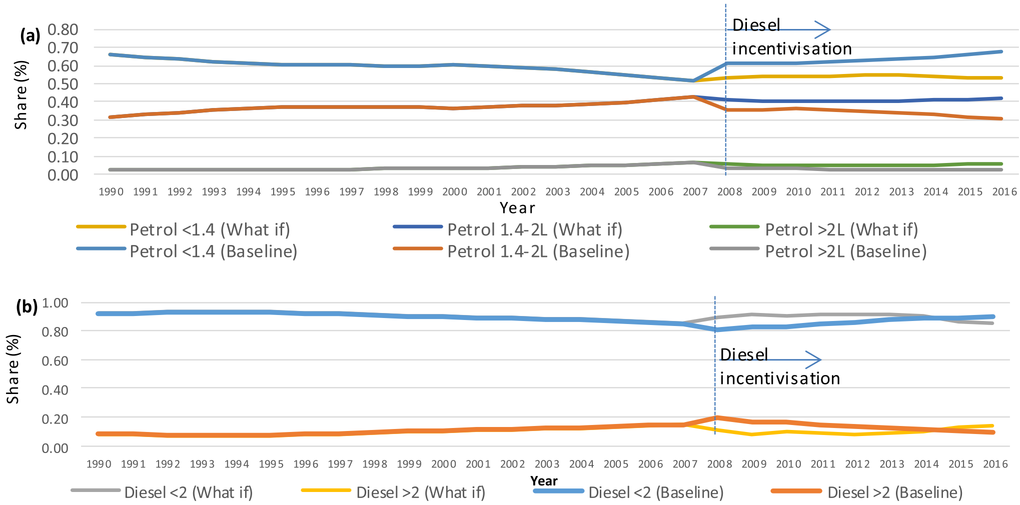

Fig. 5. Share between engine sizes: (a) Petrol, (b) Diesel.

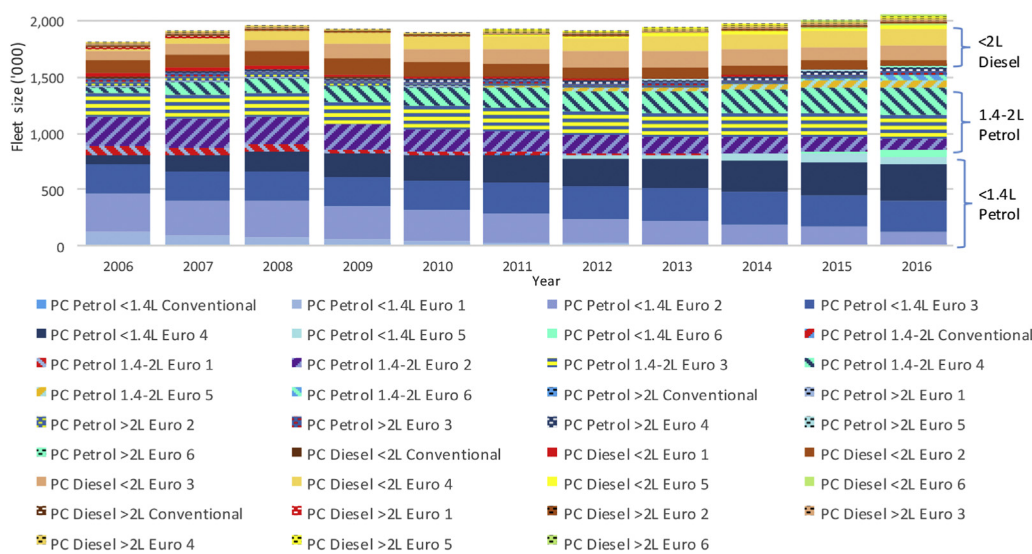

Fig. 6. Disaggregated fleet size in 'what-if' scenario.

NO_x IEFs increased for diesel >1.4 L for the years 2011–2015. However, both diesel engine sizes showed a decreasing trend. While NO_x emission for diesel <1.4 L showed a decreasing trend, it was one of the highest NO_x producing sources in comparison to the emission level of other PC categories.

The most impacting fleet category for NO_x emission was identified as diesel <1.4 L. At the same time, CO_2 IEF for this vehicle technology was the second lowest source. Thus, it is noticeable that a change in fleet size in this vehicle technology would likely have the most impact on the total fleet emission. Using this knowledge on the impact of a single vehicle category shift, the FEC framework tool was developed to control the future fleet composition.

4. Application of the FEC framework

The following steps were considered to produce an optimal fleet composition in Fig. 12 and an optimised emission scenario in Fig. 13:

Step 1: Emission ranking:

Two emission types with the highest priorities were selected, one from air pollution (NO_x) and one from climate change priorities (CO_2) (see Fig. 10). CO_2 is the primary greenhouse gas and NO_x emission is the priority emission in the air pollution reduction commitment (EPA, 2018).

Step 2: Calculate emission trade off factor (g/km):

An emission trade-off factor was calculated which was the difference or saving in the vehicle category unit in g/km of NO_x emission, as a result of switching from one type of vehicle to another. Trade-off factors were calculated for three groups: (1) Diesel <1.4 L to Petrol <1.4 L; (2) Diesel <1.4 L to Petrol 1.4–2 L; and (3) from Diesel >1.4 L to Petrol >2 L. The average emissions for these three groups over the years were 0.44 g/km, 0.44 g/km and 0.46 g/km for NO_x.

Step 3: Calculate mileage required to minimise the emission difference

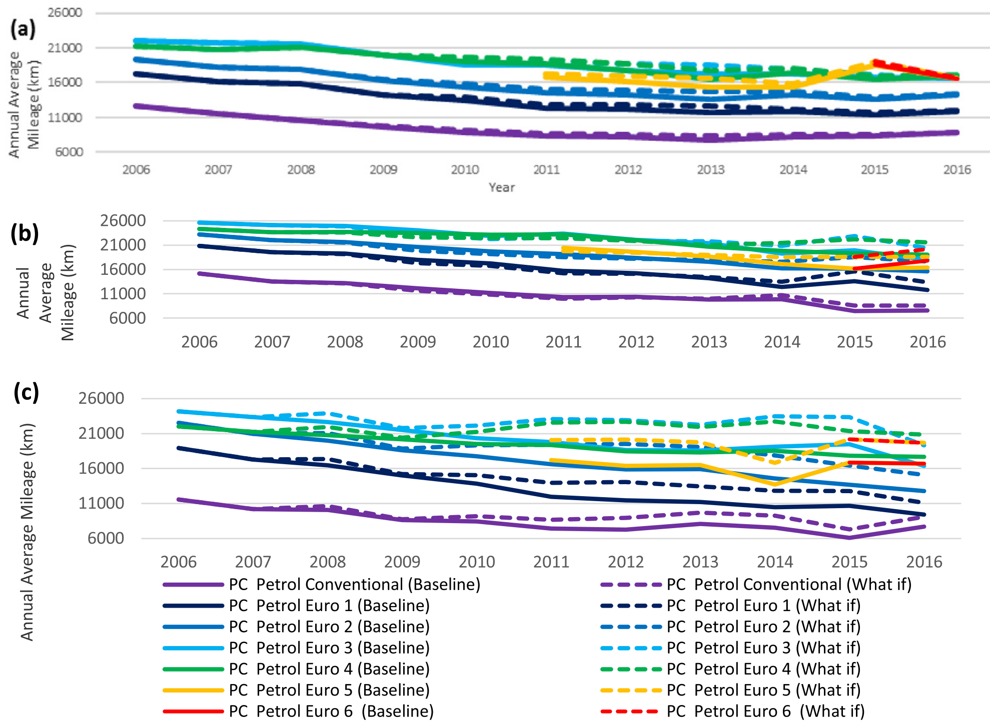

Fig. 7. Annual average mileage for petrol powered PC: (a) < 1.4 L; (b) 1.4–2 L; (c) >2 L

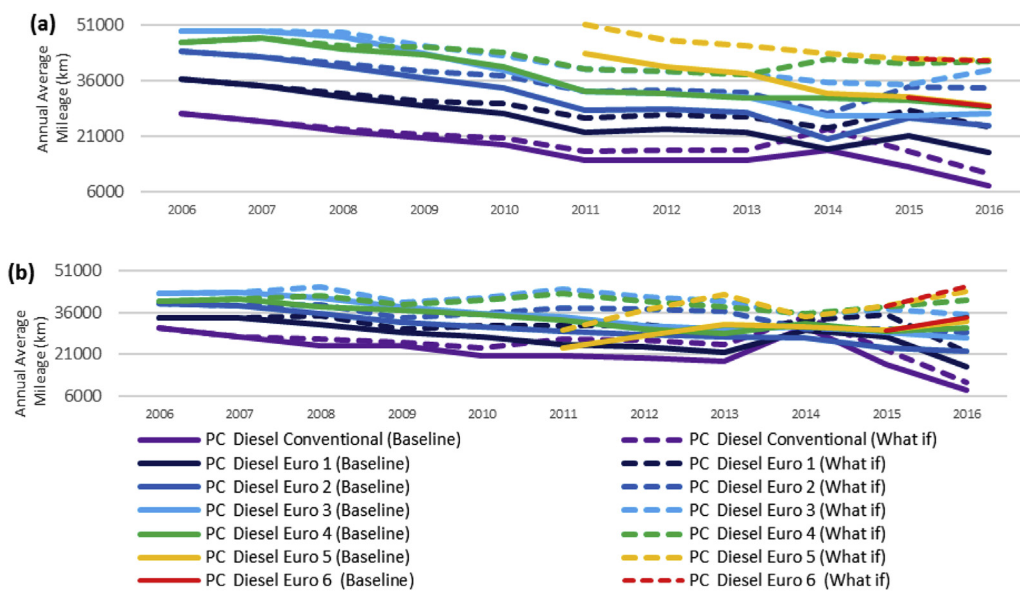

Fig. 8. Annual average mileage for diesel powered PC: (a) <2 L; (b) >2 L

Four elements were required to perform this calculation (see Annex): 1. Initial constant mileage for the starting year when emission has started to increase (2010 for NO_x); 2. Distribution of mileage for groups selected for trade-off factor calculation; 3. Baseline vehicle size distribution for the same groups; and 4. Increment of initial constant mileage in a percentage term from starting year to end year.

Step 4: Mileage shift and emission calculation

The initial mileage was selected by trial and error such that NO_x emission from all the groups closely matched the difference between the two scenarios for NO_x emission (e.g. less than 1.00 kg). Similarly, the increment of mileage was selected by trial and error to calculate a close match for all the emissions, in all the years.

Step 5: Total mileage and fleet share calculation

Calculated mileage was added and subtracted from the baseline mileage for the corresponding vehicle categories. Average mileage from the 'baseline' scenario was considered to calculate the fleet size, and then the share of vehicle categories were calculated (see

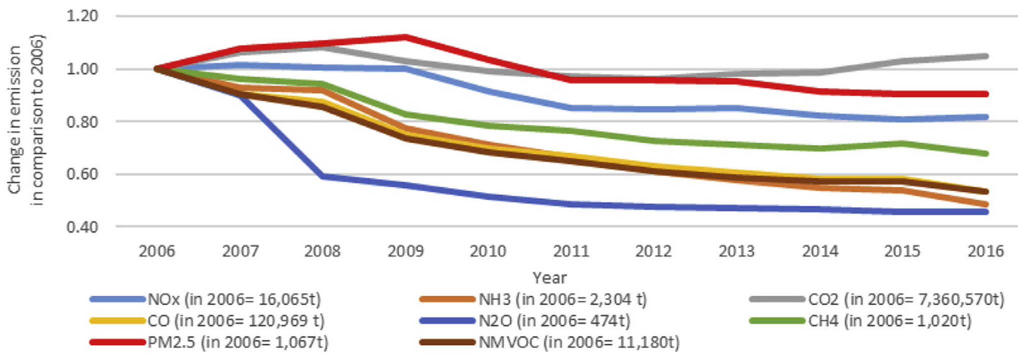

Fig. 9. Emissions in 'what-if' scenario.

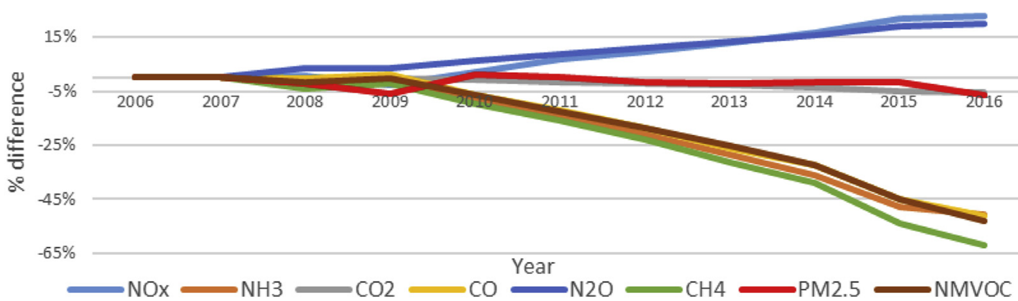

Fig. 10. Difference in emissions in 'what-if' and original scenario.

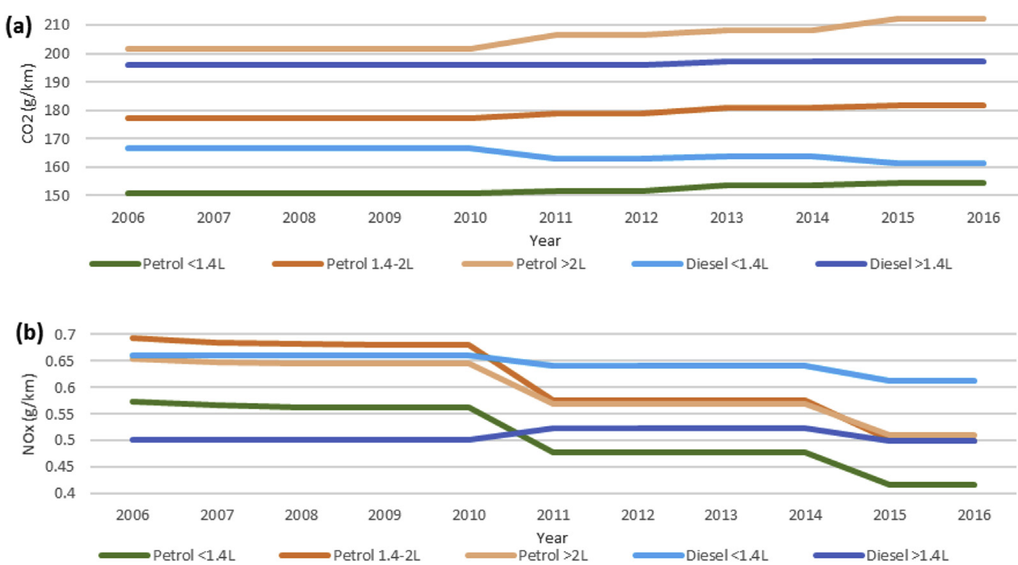

Fig. 11. (a) CO_2 and (b) NO_x implied emission factor.

Fig. 12).

For the fleet composition above, while it is expected that there will be no increase of NO_X emission and the level of NO_x emission would be the same as a scenario without dieselisation, there would be a slight increase (+1.8%) of CO_2 emission in 2016. NO_2 and $PM_{2.5}$ emissions would be reduced. The potential for $PM_{2.5}$ was not identified in Fig. 10, however, the selected fleet composition; especially shifting to petrol fuel reduced the release of $PM_{2.5}$.

5. Discussion and conclusion

Fontes & Pereira (Fontes and Pereira, 2014) reported that the fleet composition recorded in 2011 in a city in Portugal was more environmentally friendly in terms of CO_2 emission than that of 2001. However, the fleet of 2001 had a lower environmental impact considering all emission types because of a higher number of diesel vehicles. They recommended that a detailed analysis be conducted in defining transportation policies in order to minimise the impact on the environment as a whole, rather than focusing solely on CO_2 emission reduction. In the present study, the result reveal that the

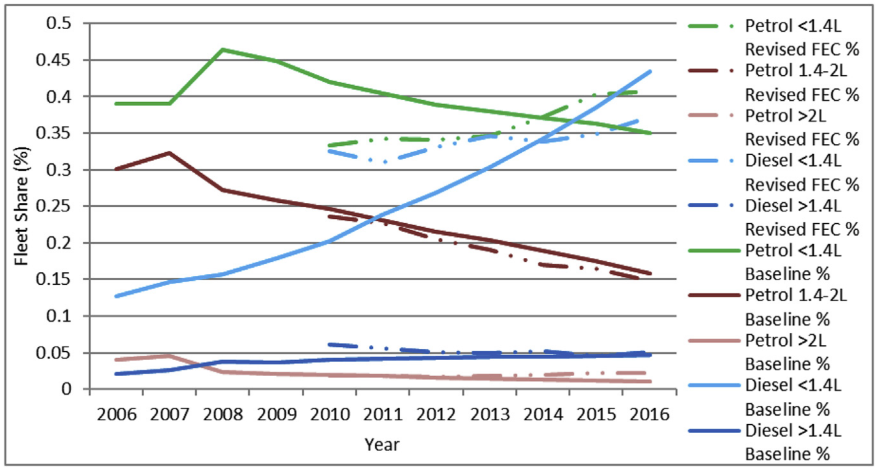

Fig. 12. Fleet composition under FEC framework with zero NO_x increase over the years.

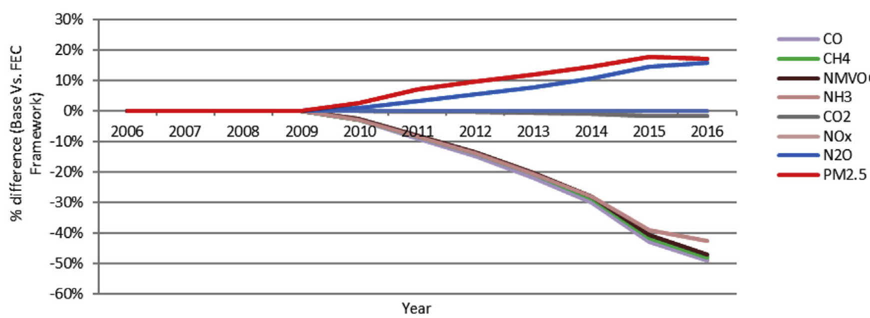

Fig. 13. Emission level under FEC framwork for no increase in NO_x emission.

combined effect of higher penetration of diesel PCs and smaller engine PCs, triggered by taxation policy, resulted in lower levels of emissions for some GHGs and air pollutants since 2008. However, the NO_x and the N_2O emissions were increased significantly in the process as a result of a higher number of diesel vehicles. This was similar to findings in eight EU cities by Degraeuwe et al. (2017) and Leinert et al. (2013). Degraeuwe et al. (2017) reported diesel cars as a major contributor to higher exposure of NO_2 concentrations among residents, and caused exceedance of the established air quality standards. Leinert et al. (2013) projected a 28% increase on NO_x emission in 2020, and a 22.8% increase was observed in 2016 in this study. If this diesel incentive was not enacted, the results of the 'what-if' scenario showed that all pollutants would have increased with the exception of NO_x and N_2O, which would have reduced. Very moderate increases in CO_2 and $PM_{2.5}$ would have occurred in the absence of the diesel incentive due to a lack of a push to purchase smaller engine vehicles, and due to the more CO_2 efficient nature of diesel engines. In the case of $PM_{2.5}$, while diesel vehicles are known to produce more of these emissions than petrol equivalents, again the lack of an incentive for smaller engines together with a smaller difference between $PM_{2.5}$ emissions in higher EURO classes, acted to result in a worse situation for $PM_{2.5}$ in the 'what-if' scenario. Purchases of larger engined petrol vehicles prevailed in the fleet in the 'what-if' scenario, increasing the emission of $PM_{2.5}$ relative to smaller engined diesels in the 'baseline' scenario. This analysis highlighted that static and infrequent changes in policy are inadequate to control emissions in an optimal manner. A dynamic and adaptable response to fleet emissions is required in light of the changing landscape of climate and air pollution targets, as well as vehicle and emissions technology, and country specific priorities and fleet status.

A dynamic Fleet Emissions Control Framework was developed in this paper which can propose practical and optimised adjustments in static taxation systems to assist in achieving the requirements of national policies on reducing emission. An emphasis is placed here on the transition period to full decarbonisation or electrification of fleets for the application of this framework.

The framework for PCs was proposed based on emissions, engine size and fuel type. An optimal fleet share and corresponding mileage in terms of offering lower harmful emission derived from the FEC Framework was developed. The modeller could rank the emission type to suit local priorities and the framework could be applied as per alternative priorities. Transport authorities may set their target for national level emission reduction as similar to the local authorities (Fuel Cells Bulletin, 2018). In this study, NO_X and CO_2 emissions were chosen as indicators. It was noticed that a 1.8%–19.3% shift of mileage from diesel to petrol vehicles from the years 2010–2016, might have kept NOx emission to the same level at the cost of a 1.8% increase in CO_2 emission in 2016. From the framework, fleet share and mileage were derived which can be used as an indicator to control the future fleet evolution. The analysis of the potential future from these data can be extended in relation to the macroeconomic forecasts.

However, to implement a change in the fleet in future, the elasticity of motor tax and registration tax to engine size of the vehicle require estimation through further research. Taxes can then be adjusted based on the elasticity and indication of the fleet from the framework. The framework should be reviewed every three to five years to enact changes and to address those through further analysis. The framework was developed for conventional vehicles;

however, it can also be made more complex with addition of new PC technologies (e.g. electric or hybrid vehicles).

The results of this investigation highlight that incentivising one fuel type over another, or more broadly one vehicle category over another, is a complex process with potentially positive and negative outcomes. The results highlight that either incentivising diesel or petrol each have negative consequences. Policy should instead incentivise a fleet composition which optimises the total emission. Further research is required to develop such an optimisation tool which is linked to reasonable and regular policy adjustments.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.04.094.

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